SeaFlux-CDR: Developing a multi-platform remotely sensed turbulent flux climate data record

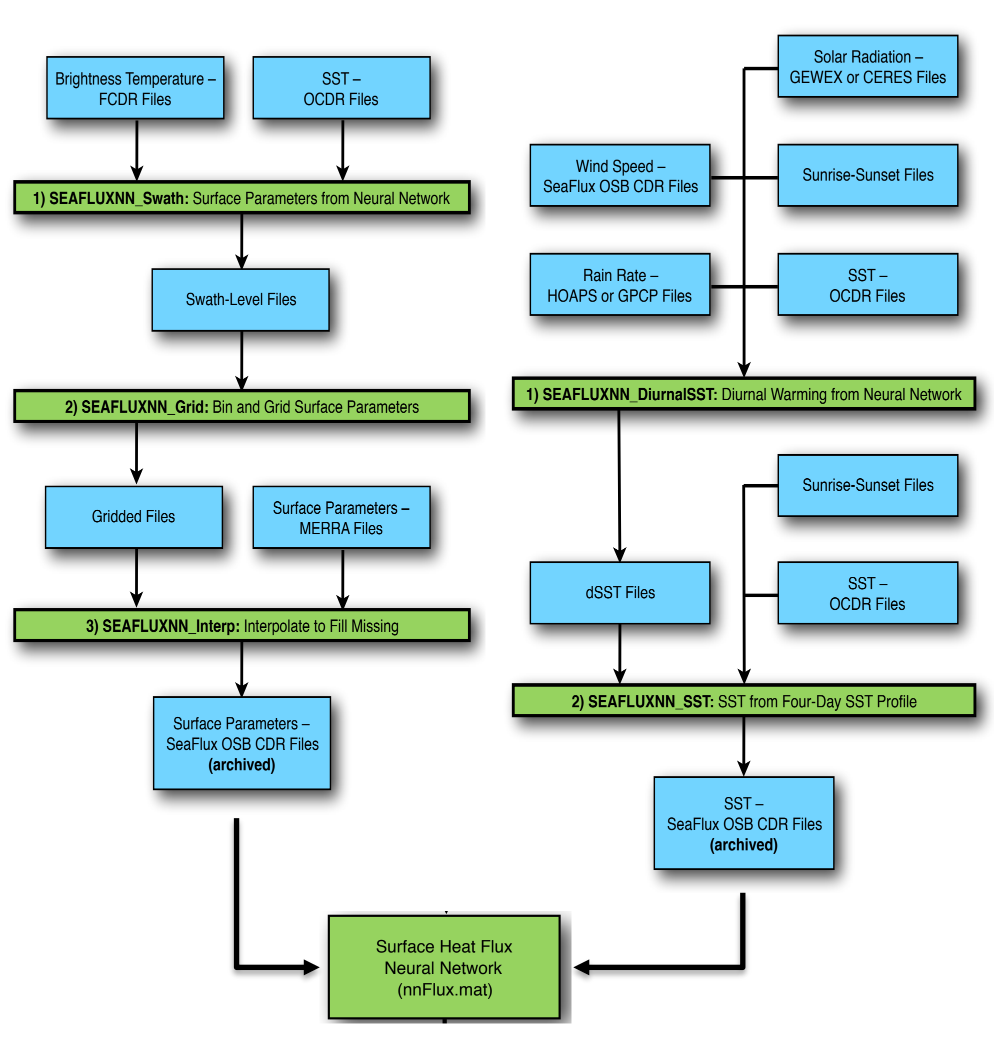
Carol Anne Clayson[1], Jeremiah Brown[2], J. Brent Roberts[3]

[1]WHOI , [2]Principal Scientific Group,[3]NASA MSFC

Key Points

- SeaFlux-Climate Data Record (SeaFlux-CDR) is an ocean surface turbulent flux climate data record developed with near-surface meteorology derived from passive microwave satellite observations. This dataset represents a significant advance over an earlier (SeaFlux Version 1) release.
- SeaFlux-CDR had been developed to address two key aspects of a climate data record, longevity and stability. Near-surface meteorology has been estimated using SSM/I and SSMIS Fundamental Climate Data Records (FCDR) microwave observations that have been intercalibrated.
- A novel Model-based Interpolation (MoBI) approach has been applied to generate the surface turbulent fluxes and associated values at 3-hourly temporal and 0.25°x0.25° spatial resolution for the period 1988-2015.

Dataset Production

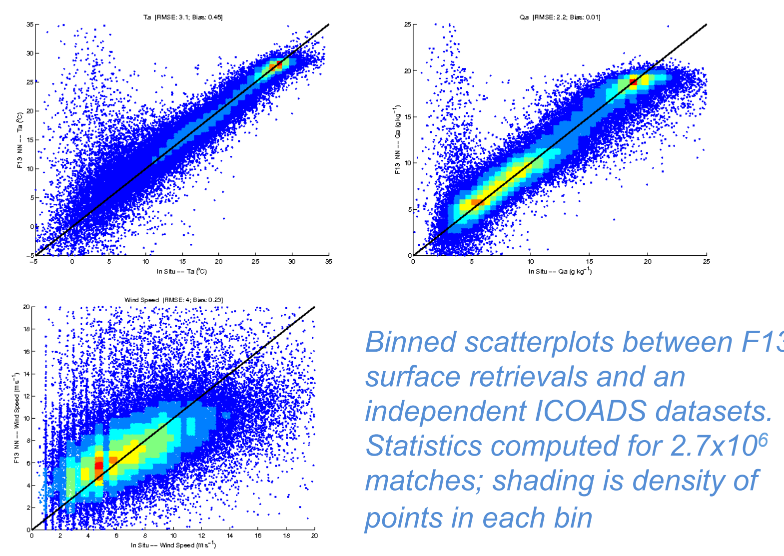


SeaFlux NN Swath
- Compute swath level retrievals of 10m wind speed, air temperature, and specific humidity using FCDR SSM/I and SSMIS trained neural networks.

SeaFlux NN Grid -> SeaFlux NN Interp
- Bin and average bulk variable retrievals onto an equal-angle 0.25°x0.25°, 3-hourly grid.
- Apply model-based interpolation to fill in missing observational gaps.

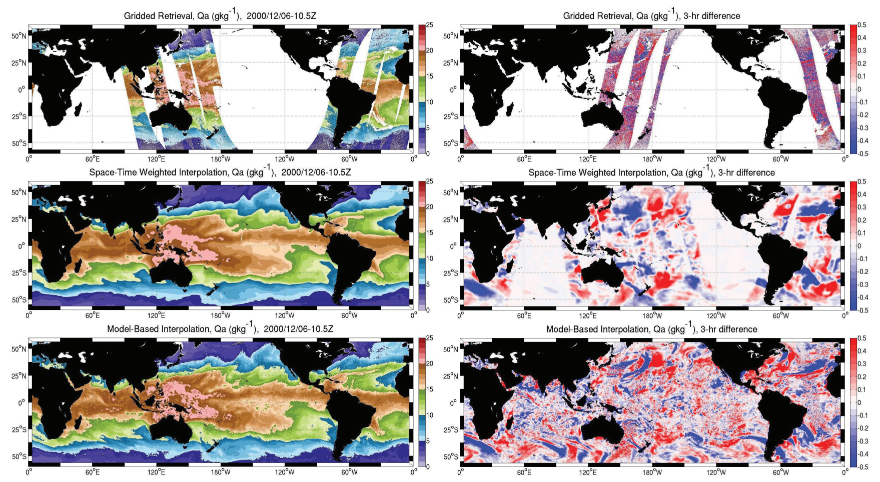
SeaFlux NN Diurnal SST -> SeaFlux NN SST
- Compute diurnal sea surface temperature (SST) warming estimate based on daily average wind speed, rain rate, and shortwave radiation.
- Generate a diurnally varying SST by superimposing a parameterized diurnal cycle on the foundation SST that accounts for sunrise and sunset times of each location.

Flux Computation
- Estimate fluxes using a neural network emulation of the COARE 3.0 bulk flux algorithm.



Binned scatterplots between F13 surface retrievals and an independent ICOADS datasets. Statistics computed for 2.7x10^6 matches; shading is density of points in each bin

Retrieved parameter evaluation against ICOADS
- Small global biases for each of the parameters
- Performs best in most typical conditions as indicated by sample density (yellow to red colors)
- Some conditional biases remain for high specific humidity



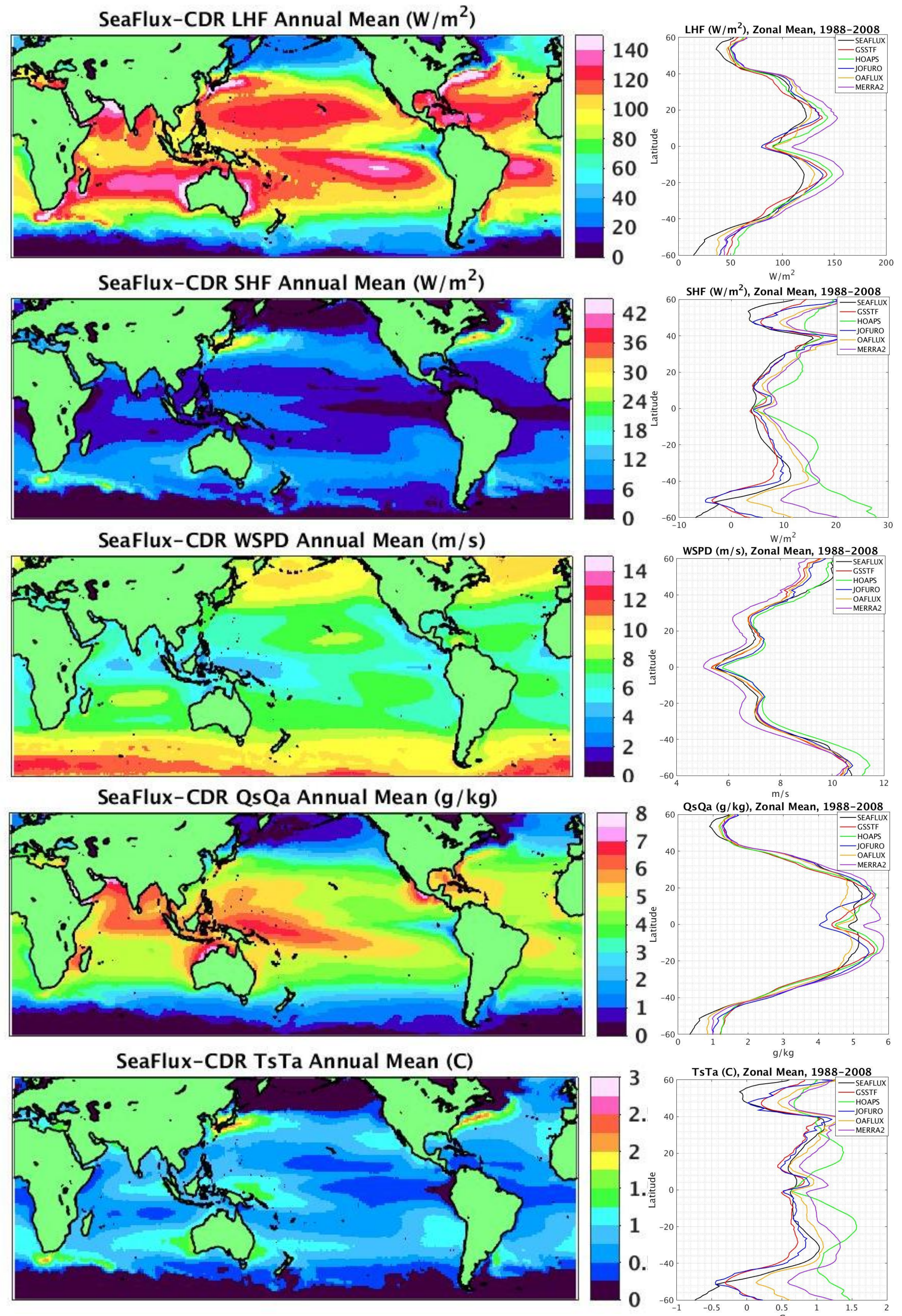
(left) Examples of the gridded, but non-interpolated surface humidity (Qa) retrieval, results using a simple space-time window weighted interpolation, and the results of MoBI. (right) Examples of 3-hr differences of the same fields. Note how MoBI more smoothly captures the 3-hr evolution of high-latitude synoptic systems.

Model-based Interpolation (MoBI)

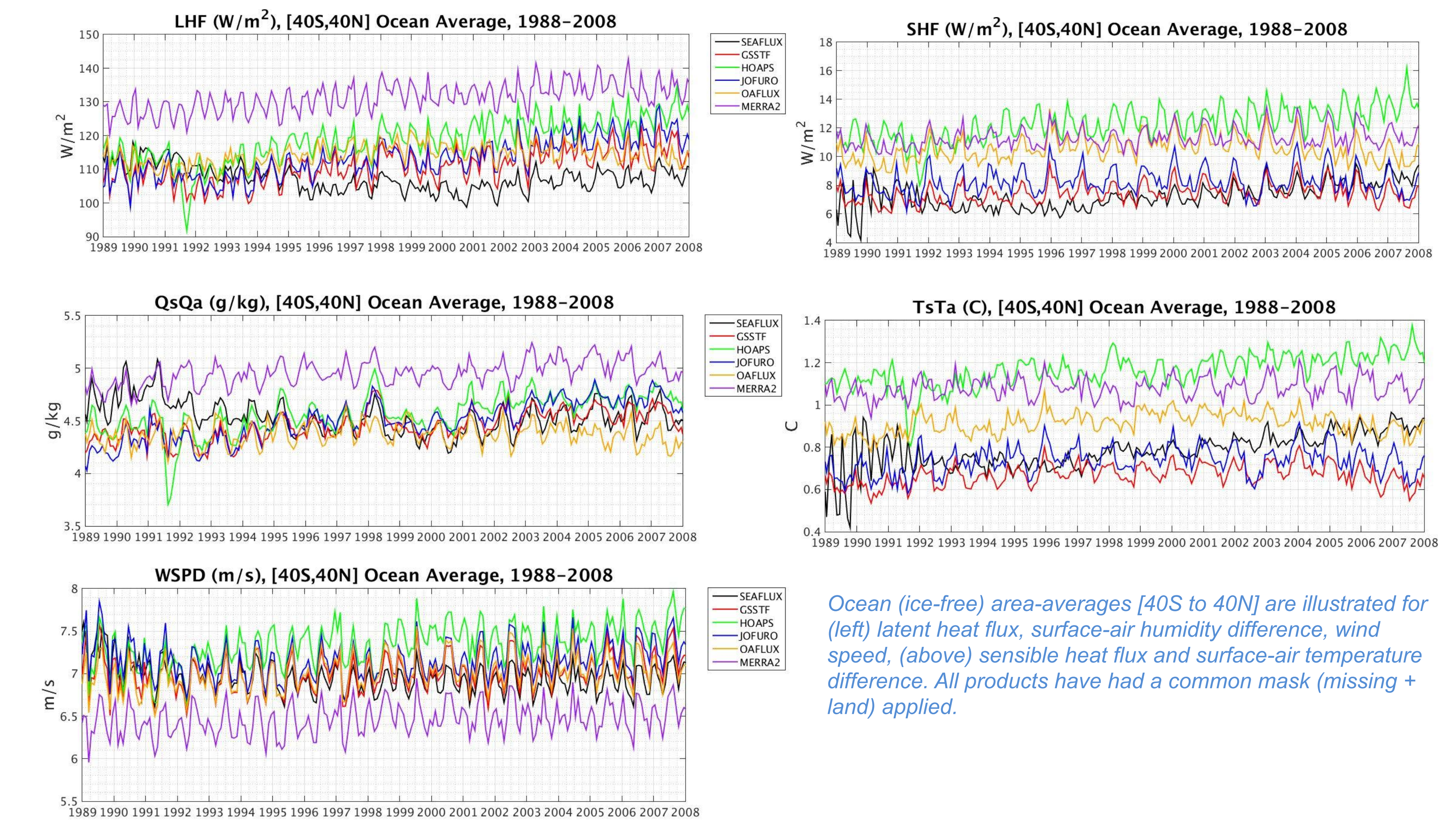
Analysis equation: $X_t = M_t + \Delta_A + (n/N\ \Delta_B - n/N\ \Delta_A) = M_t + (1-f)\ \Delta_A + (f)\ \Delta_B$

- Interpolates to unknown point (t) between observed satellite estimates at times A & B. Uses a weighted mean based on the difference between the satellite and model (MERRA-2) at observations and temporal distance between the observed points.
- Better maintains local spatial structure and temporal evolution than traditional space-time window based weighted interpolation.

SeaFlux-CDR Climatology and Variability



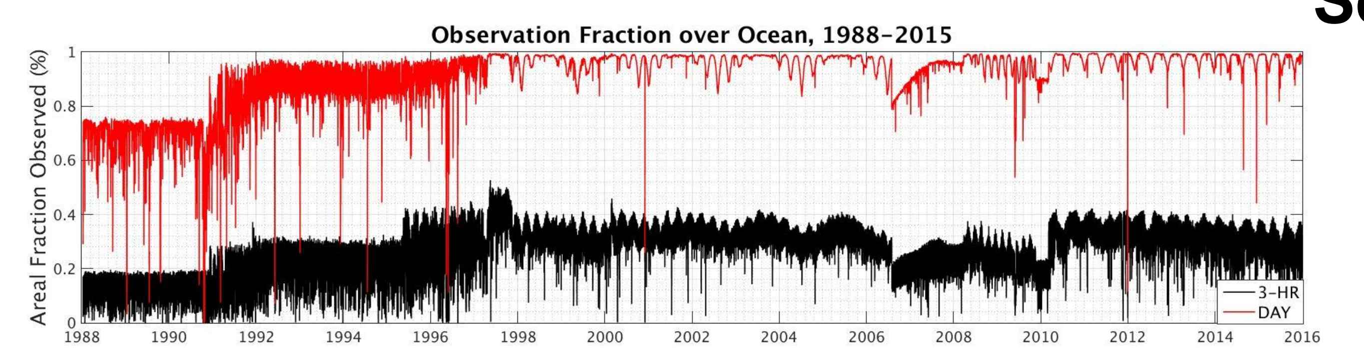
(left) Annual mean climatologies (1988-2008) of the SeaFlux-CDR for (top to bottom), latent heat flux (LHF), sensible heat flux (SHF), wind speed (WSPD), surface-air humidity difference (QsQa), surface-air temperature difference (TsTa). Also shown are zonal means of several satellite and reanalyses products. All products have had a common (monthly) missing mask applied. Note that while MERRA2 is used in MoBI, the CDR remains distinct.



Ocean (ice-free) area-averages [40S to 40N] are illustrated for (left) latent heat flux, surface-air humidity difference, wind speed, (above) sensible heat flux and surface-air temperature difference. All products have had a common mask (missing + land) applied.

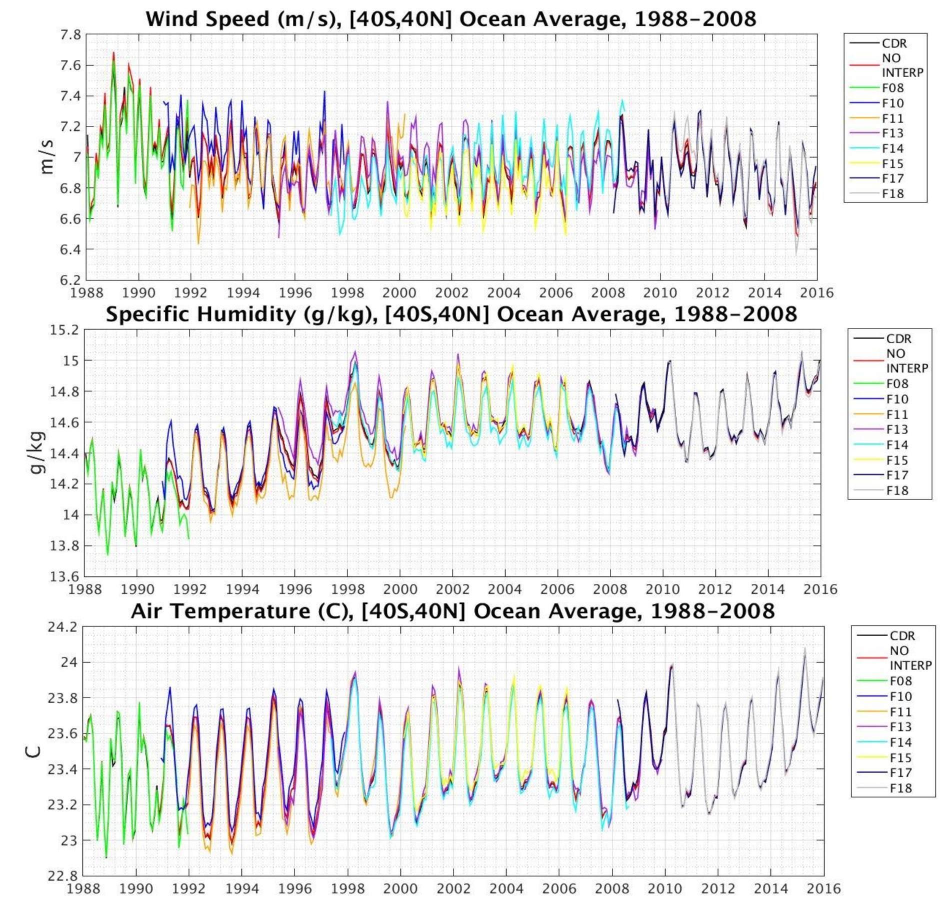
- Primary climatological features of the SeaFlux-CDR include enhanced turbulent latent and sensible heat fluxes over the western boundary currents (WBCs), subtropical ridges, and local minima over the Pacific and Atlantic equatorial cold tongues. These patterns are controlled to first order by the climatological mean components of the bulk variables
- Zonally, the SeaFlux CDR is broadly consistent with other "latest-generation" satellite based products with the exception of a muted LHF in the subtropics as driven by weaker QsQa. Note that OAFlux has even weaker QsQa but is compensated by stronger wind speeds.
- Area-averages indicate the CDR LHF and SHF are consistent with other satellite products. MERRA-2 remains an outlier as a result of systematically lower wind speeds. The CDR SHF exhibits a weak trend as a result of increasing surface-air temperature differences. The CDR wind speeds exhibit almost zero long term trend. The CDR LHF shows a small decrease at the beginning of the record but remains relatively stable thereafter while other products diverge as a result of an increasing trend in QsQa.

SeaFlux-CDR Stability



Fraction of ocean (ice-free) area that is observed every 3-hours (black) or at least once every day (red) by the available stream of SSM/I and SSMIS sensors. Note a small annual cycle that is a results of changing (ice-free) area that impacts the total area to be observed – i.e. a constant observational area observing a smaller or larger total area.

- Changes in sampling due to the availability of sensors are prevalent. All current passive microwave-based turbulent fluxes must address this issue. In addition to absolute fractional area variability, equatorial crossing times also change which can generate artificial variability.
- Prior to about 1996, the sampling remains fairly sparse and shows much sensitivity (high noise) even in the daily observed fraction. After the ingest of F14, the observed fraction becomes much more stable. The loss of F15 in 2006 results in a minor reduction before recovering as F17 becomes available.



- The MoBI interpolation shows no tangible impact on altering the climatological variability (e.g. sub-seasonal to annual or longer) compared to the un-interpolated (i.e. raw gridded) products. This is illustrated by the near overlap of the CDR and "No Interp" area-averaged time series (see left).
- Wind speeds appear to have the most sensitivity to individual input sensors, with F14 standing out. We note that diurnal sampling characteristics change with sensor so at least some of the differences may be physical.
- F8 remains a challenge as it is more noisy and a modified neural network algorithm had to be utilized.

Near-surface retrievals of wind speed, specific humidity, and air temperature are shown for the period 1988-2015 as estimated for several different "flavors" of the CDR. Specifically, the full CDR (black) is compared with that based only on observed samples (no MoBI interpolation; red) and also individual SSM/I and SSMIS sensors (colors as indicated).